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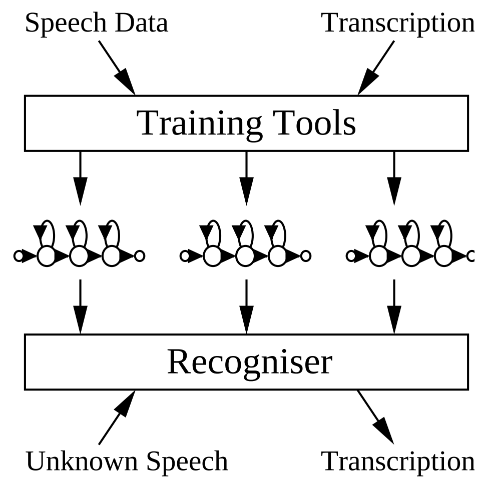
HMM tutorial 5

by Dr Philip Jackson

- Simple example
- Use of HMMs
  - Introduction to HTK
- Practical issues
  - Training and testing
- Application to speech
  - Isolated words
  - Continuous
- Summary



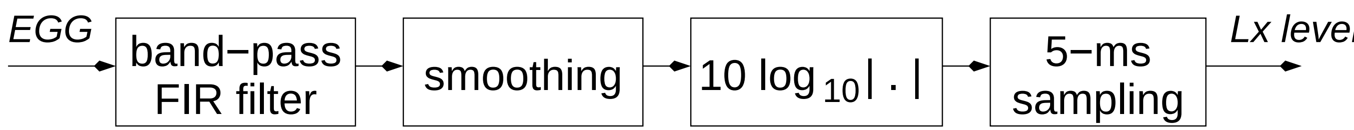
* Figures taken from Young et al. (1997)

http://www.ee.surrey.ac.uk/Personal/P.Jackson/tutorial/

Illustrative example

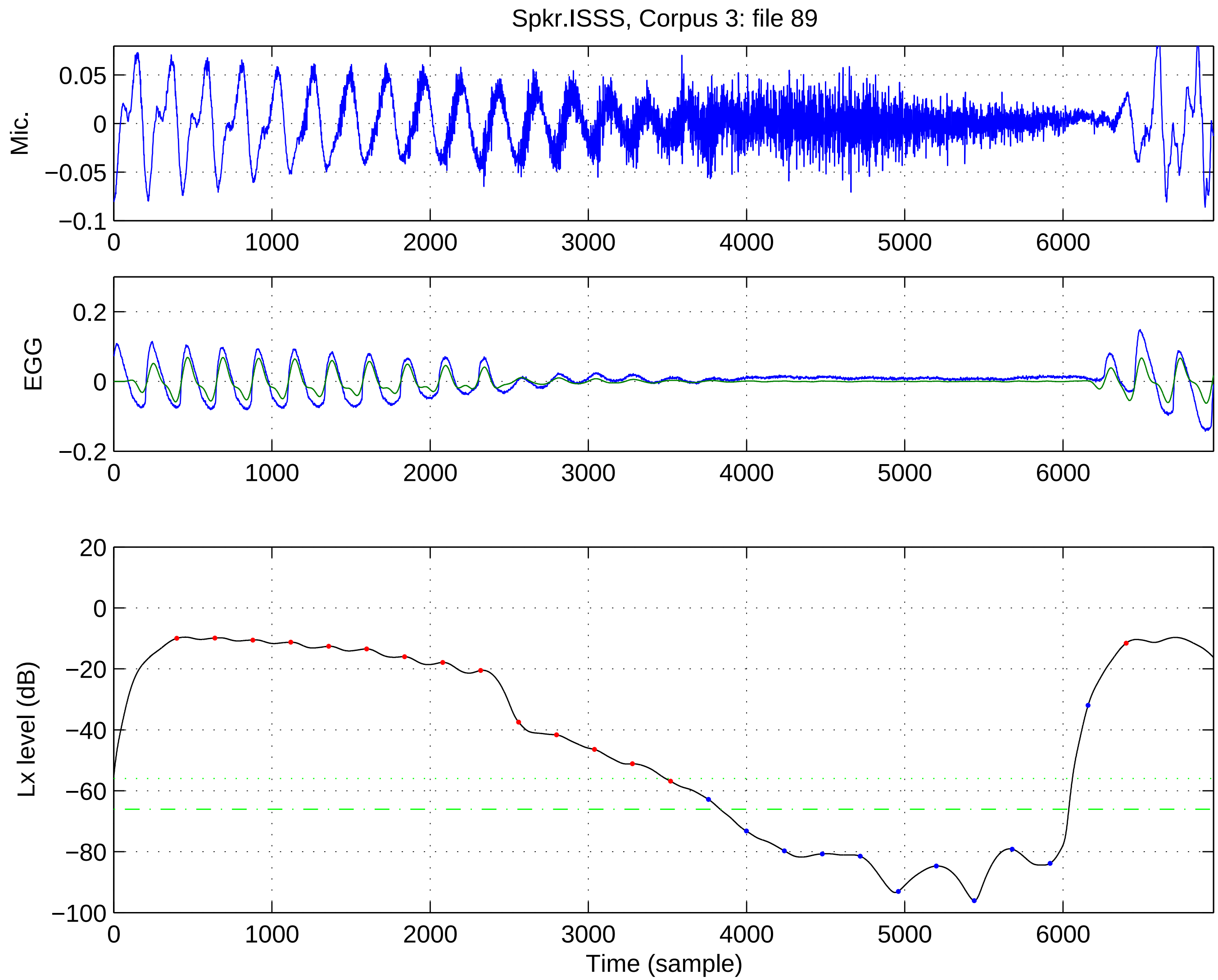
Aim:

to provide an objective labelling of voiced and unvoiced regions during fricative speech.



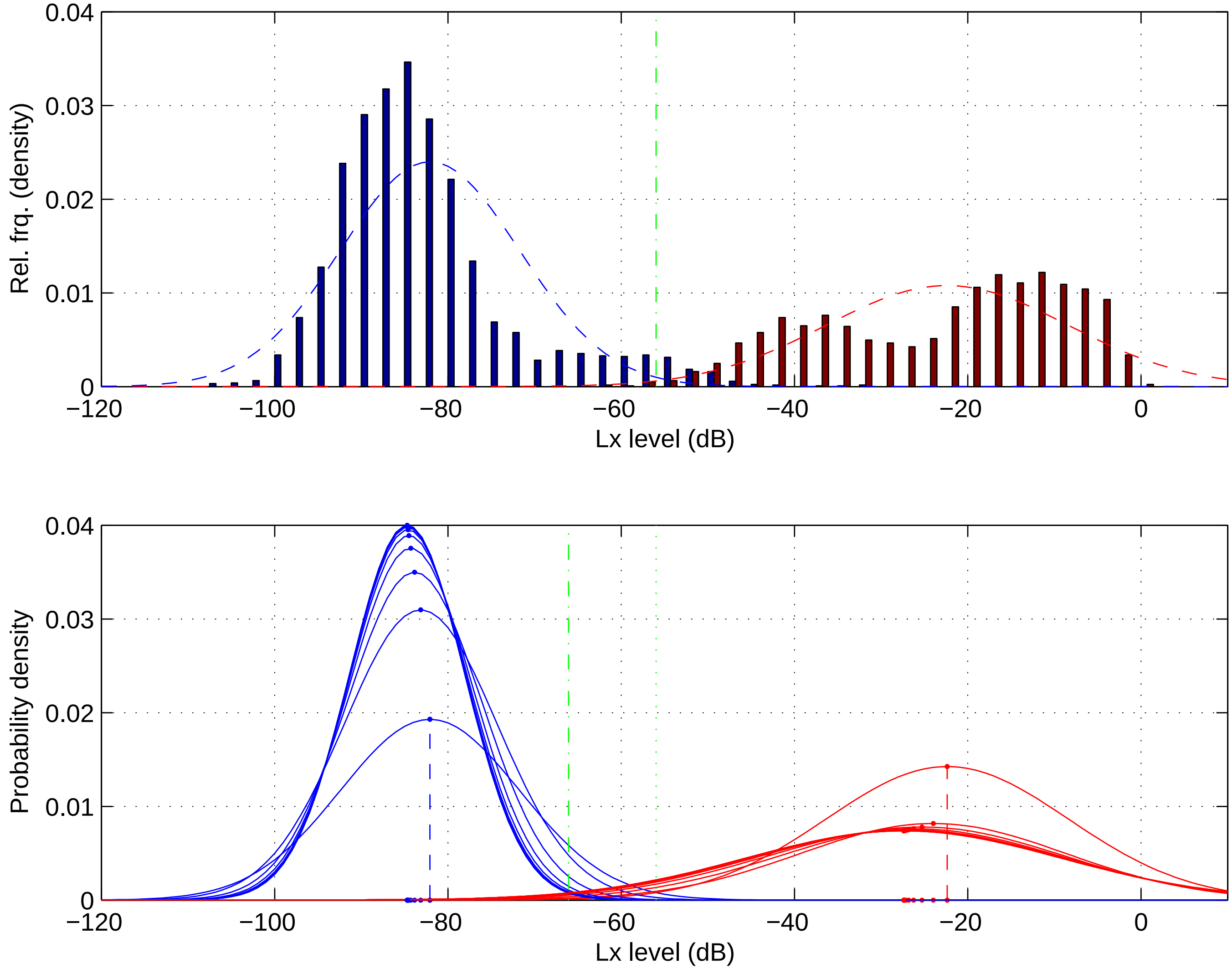
Processing of EGG signal to give Lx-level features.

Feature extraction front end



From top: acoustic waveform (top) of VFV utterance of devoiced /zh/; original and band-passed EGG waveforms; derived Lx level.

Effect of training



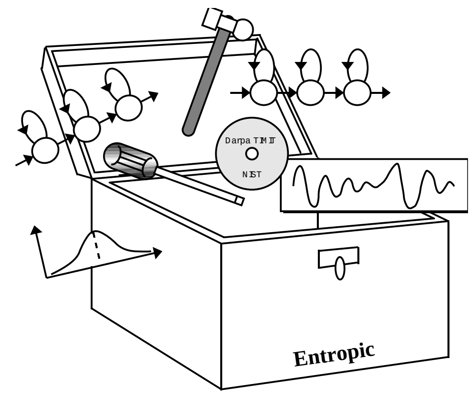
From top: histograms of Lx level classified manually with initial models; convergence of model re-estimation (from dashed start).

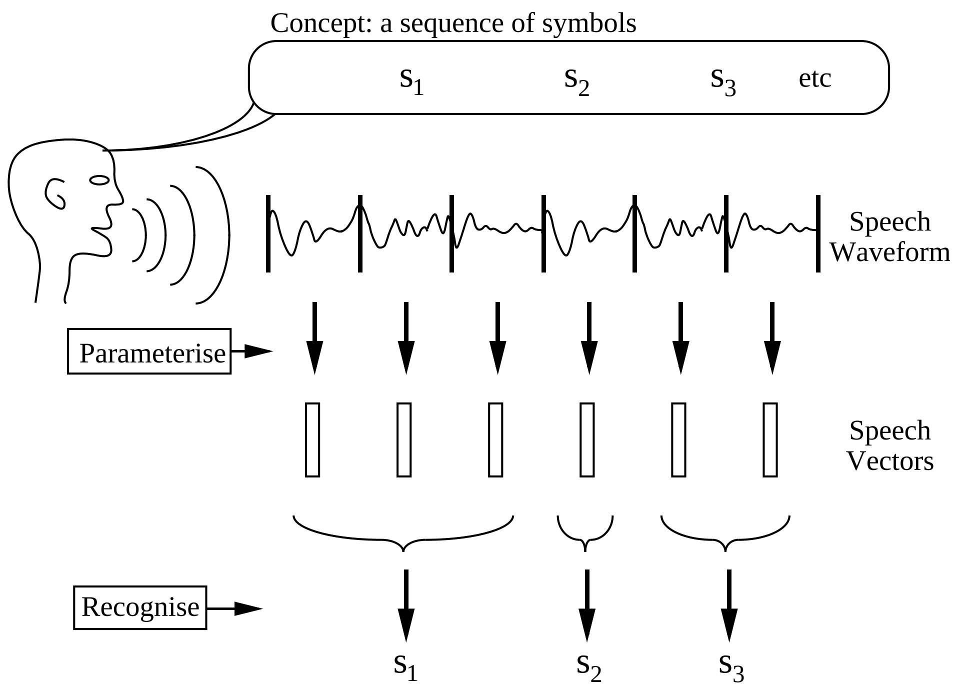
Example summary

- Hand labelled training data
- Initialised model
- Trained model
- Decoded with model to determine voiced/unvoiced boundaries
- Timing results used in analysis

Tools for using HMMs

- Data preparation
- Training
- Testing
- Analysis





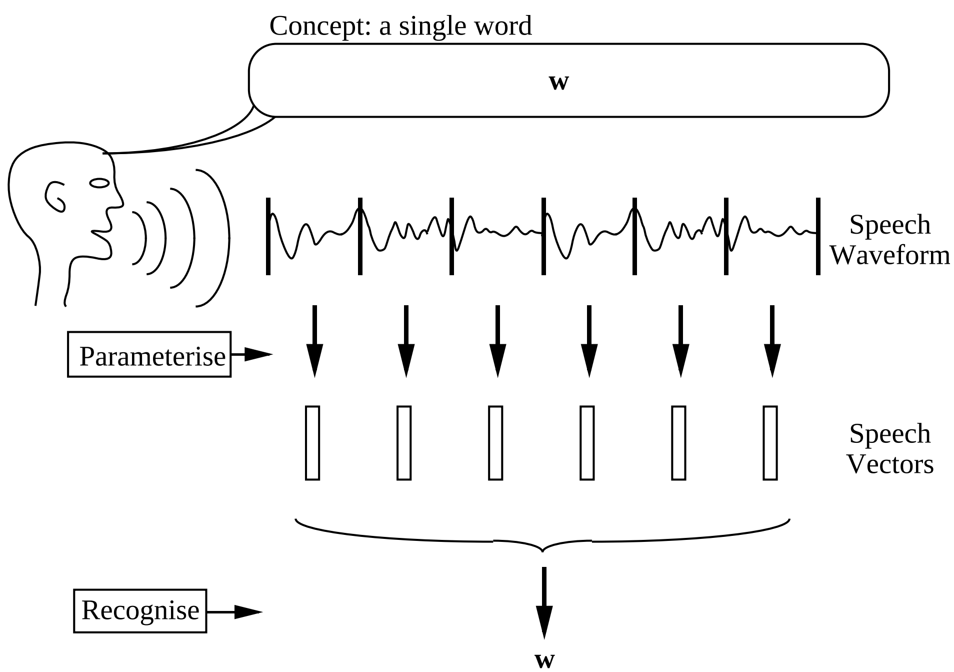
Message encoding and decoding.*

Isolated word recognition

The problem is to find

$$\arg\max_i \{P(w_i|\mathcal{O})\}, \quad (1)$$

where, according to Bayes, $P(w_i|\mathcal{O}) = \frac{P(\mathcal{O}|w_i)P(w_i)}{P(\mathcal{O})}$.

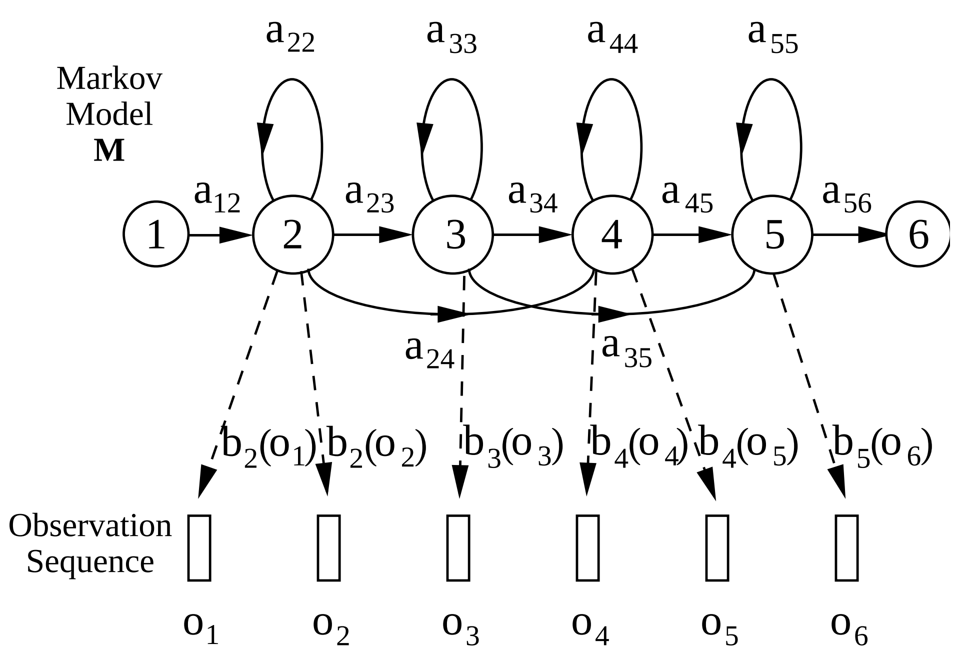


Isolated word problem.*

The hidden Markov model

In this case, we assume

$$
\begin{aligned}
P(\mathcal{O}|w_i) &= P(\mathcal{O}|\lambda_i) && (2) \\
&= \arg\max_{X} \pi_{x_1}\, b_{x_1}(o_1). \prod_{t=2}^{T} a_{x_{t-1}x_t}\, b_{x_t}(o_t).
\end{aligned}
$$



The Markov generation model.*

Building the grammar

Example utterances:

Dial three three two six five four

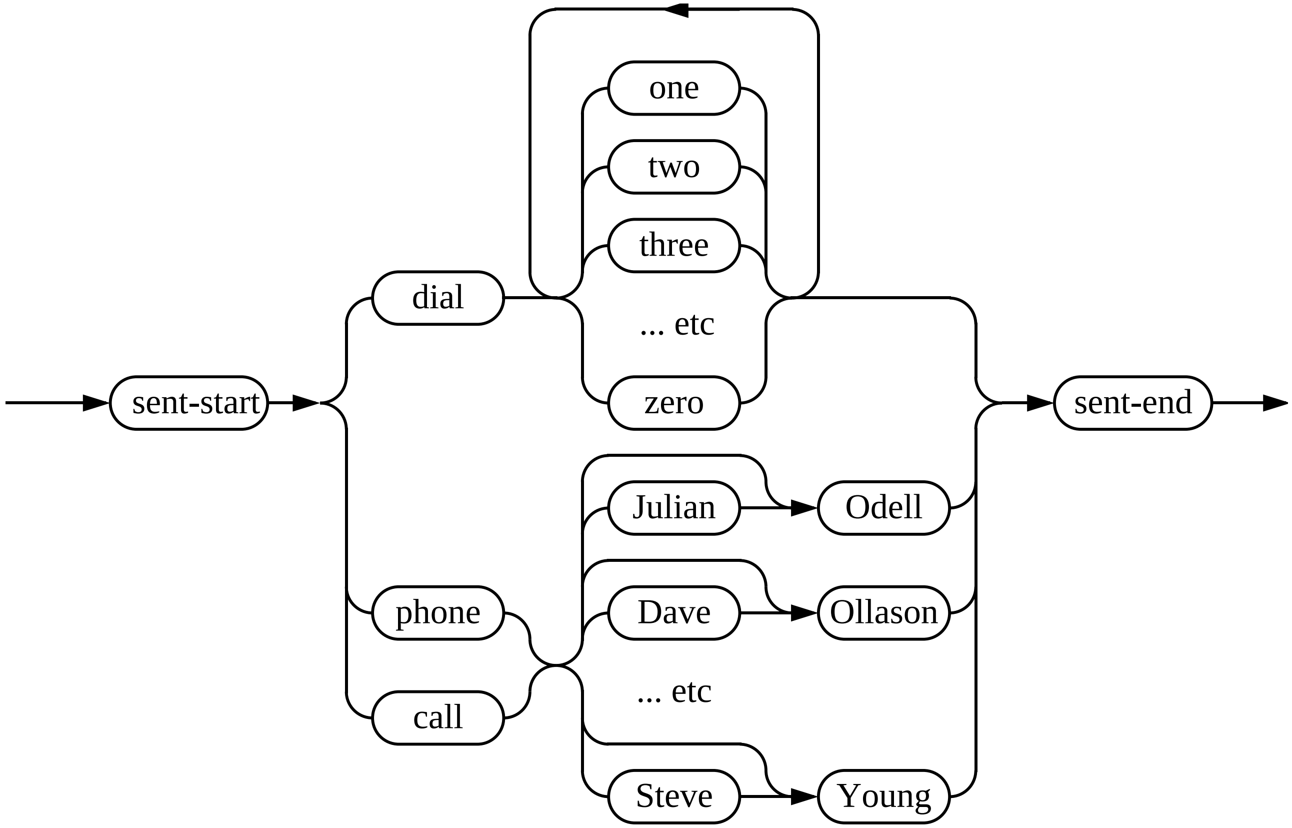
Phone Woodland

Call Steve Young

Task grammar:

```
$digit = ONE | TWO | THREE | FOUR | FIVE |
         SIX | SEVEN | EIGHT | NINE | OH | ZERO;
$name  = [ JULIAN ] ODELL |
         [ DAVE ] OLLASON |
         [ PHIL ] WOODLAND |
         [ STEVE ] YOUNG;
( SENT-START ( DIAL <$digit> | (PHONE|CALL) $name) SENT-END )
```

Key: | alternatives, [·] optional, <·> one or more reps.

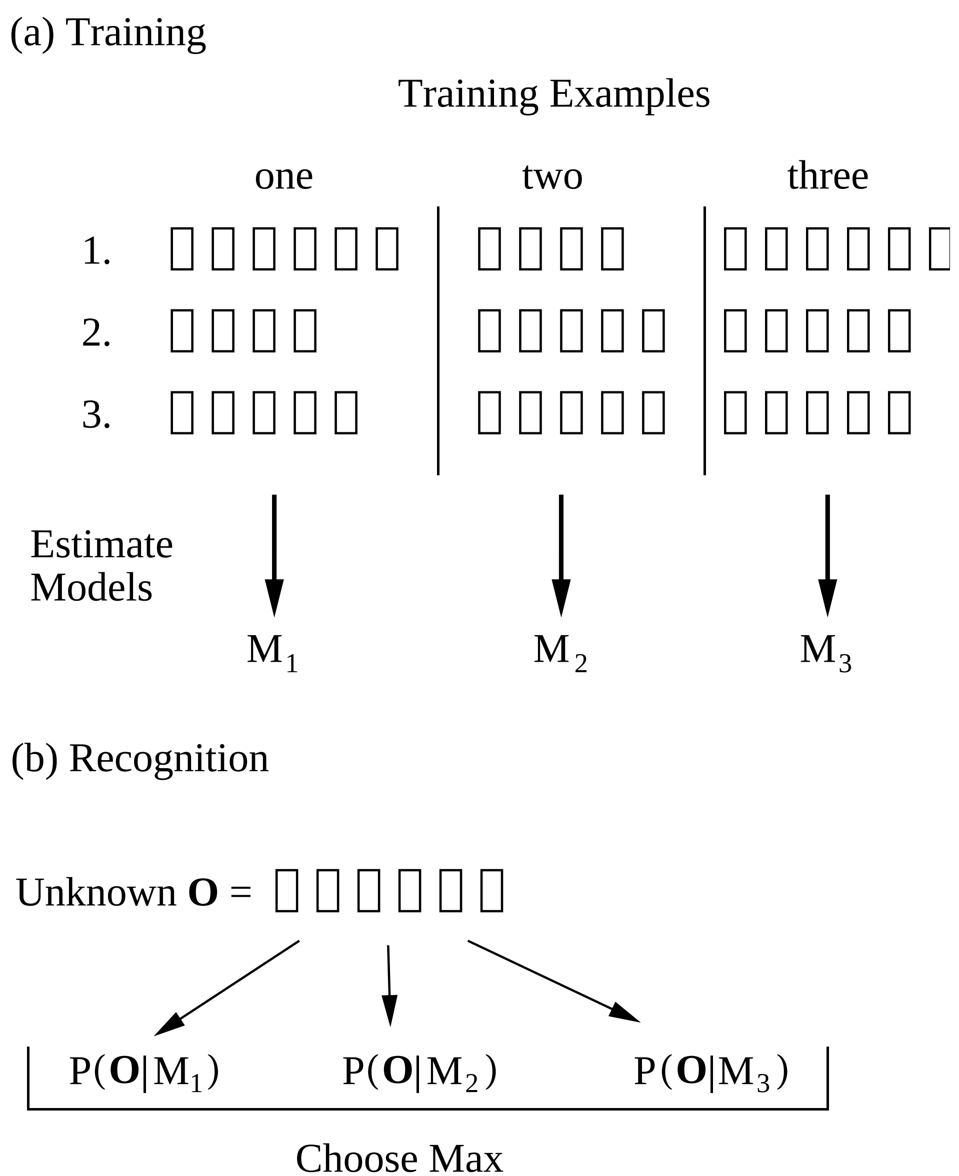


Grammar for voice dialling.*

Dictionary

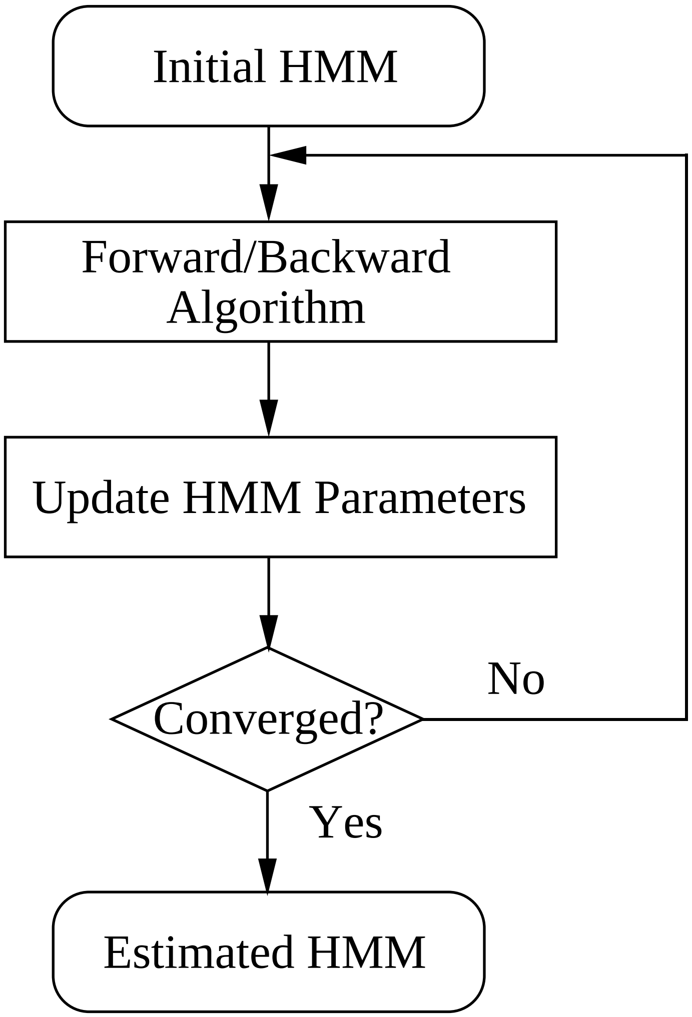
```
ONE         w ah n sp
TWO         t uw sp
THREE       th r iy sp
FOUR        f ao sp
FOUR        f ao r sp
...
```

Training and test data



Using HMMs for isolated word recognition.*

Re-estimation process

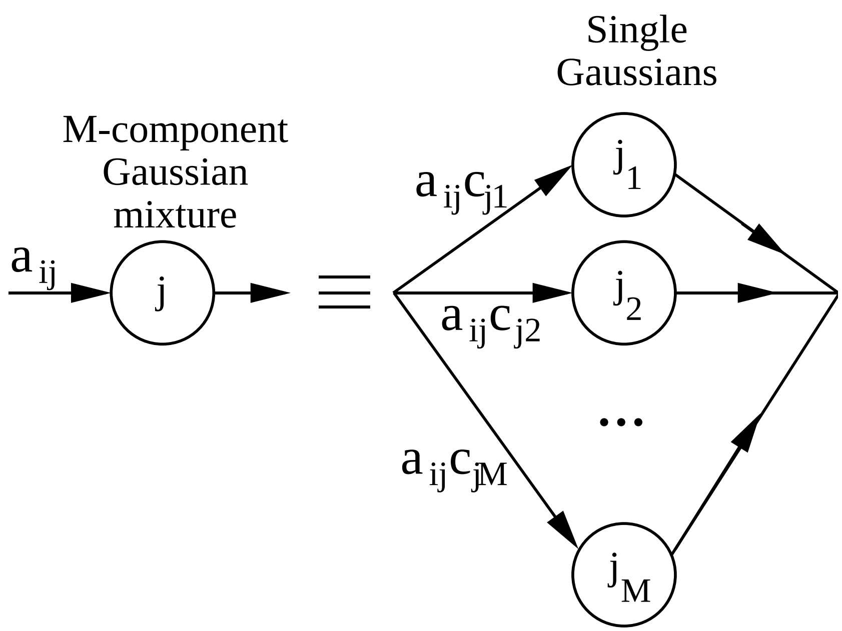


Isolated unit re-estimation.*

Output probabilities

Recall, for a Gaussian mixture, the output probability

$$b_j(\mathbf{o}_t) = \sum_{m=1}^{M} c_{jm} \mathcal{N}\left(\mathbf{o}_t; \boldsymbol{\mu}_{jm}, \boldsymbol{\Sigma}_{jm}\right) \tag{3}$$



Representing a mixture of Gaussians.*

Viterbi re-estimation:

means $\qquad \hat{\boldsymbol{\mu}}_{jm} = \frac{\sum_{t=1}^{T} \psi_t(j,m)\mathbf{o}_t}{\sum_{t=1}^{T} \psi_t(j,m)},$

variances $\qquad \hat{\boldsymbol{\Sigma}}_{jm} = \frac{\sum_{t=1}^{T} \psi_t(j,m)(\mathbf{o}_t - \boldsymbol{\mu}_{jm})(\mathbf{o}_t - \boldsymbol{\mu}_{jm})'}{\sum_{t=1}^{T} \psi_t(j,m)},$

weights $\qquad \hat{c}_{jm} = \frac{\sum_{t=1}^{T} \psi_t(j,m)}{\sum_{t=1}^{T} \psi_t(j)},$

where $\psi_t(j, m)$ and $\psi_t(j)$ are binary indicator functions.

Baum-Welch re-estimation:

means $\qquad \hat{\boldsymbol{\mu}}_{jm} = \frac{\sum_{t=1}^{T} \gamma_t(j,m)\mathbf{o}_t}{\sum_{t=1}^{T} \gamma_t(j,m)},$

variances $\qquad \hat{\boldsymbol{\Sigma}}_{jm} = \frac{\sum_{t=1}^{T} \gamma_t(j,m)(\mathbf{o}_t - \boldsymbol{\mu}_{jm})(\mathbf{o}_t - \boldsymbol{\mu}_{jm})'}{\sum_{t=1}^{T} \gamma_t(j,m)},$

weights $\qquad \hat{c}_{jm} = \frac{\sum_{t=1}^{T} \gamma_t(j,m)}{\sum_{t=1}^{T} \gamma_t(j)},$

where $\gamma_t(j, m)$ is as before and $\gamma_t(j) = \frac{\alpha_t(j)\,\beta_t(j)}{P(\mathcal{O}|\lambda)i)}$.

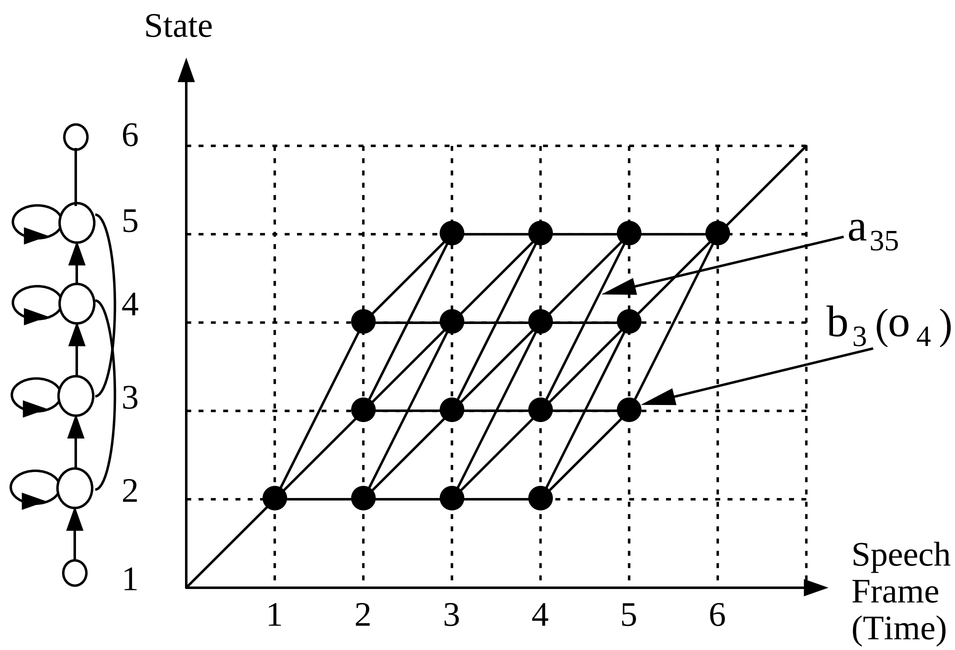
Training procedure

1. initialise accumulators for all HMMs' parameters

2. read the next training utterance

3. join HMMs in sequence to make composite HMM

4. calculate forward & backward probabilities



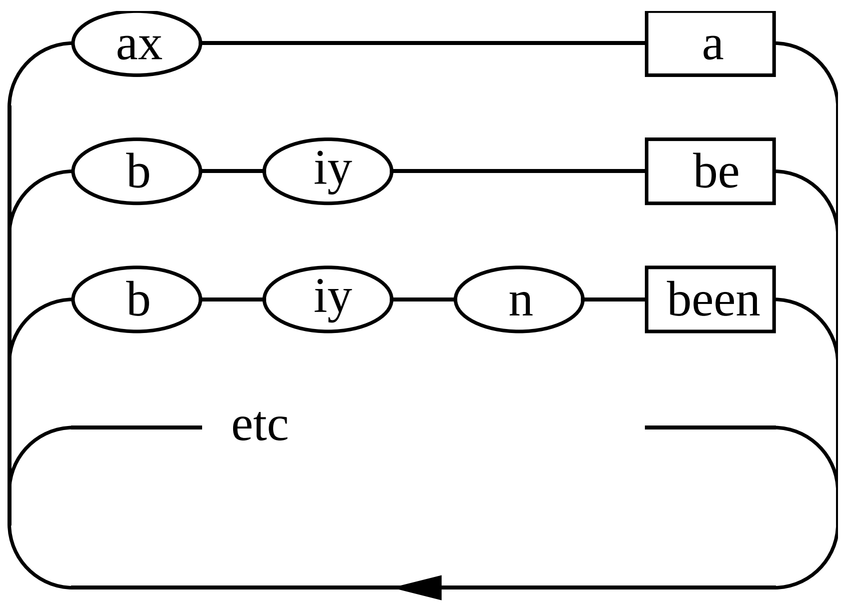
The Viterbi algorithm for isolated word recognition.*

for Continuous speech recognition

5. use forwd/backwd probs to increment accumulators

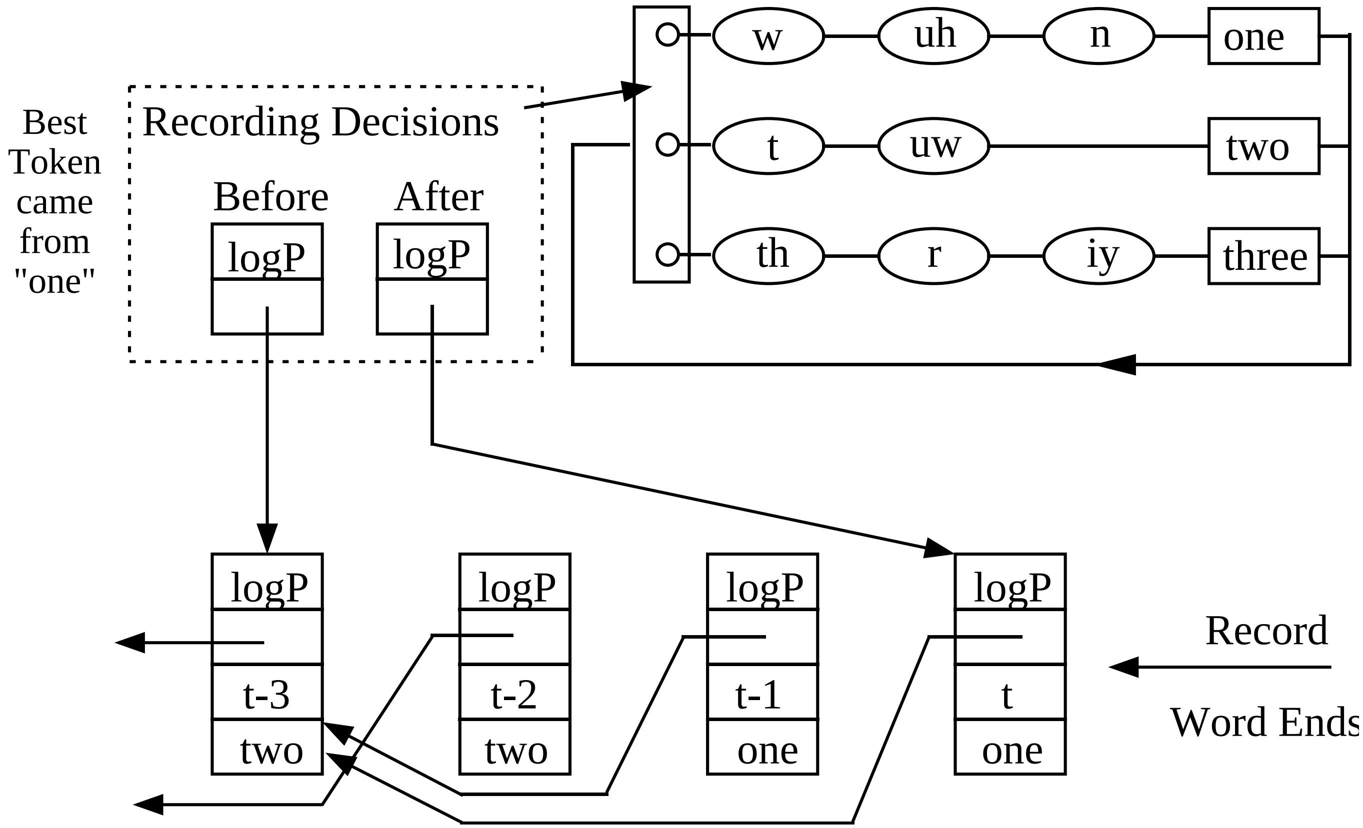
6. repeat from step 2 until all utterances processed

7. use accumulators to update parameters for all HMMs



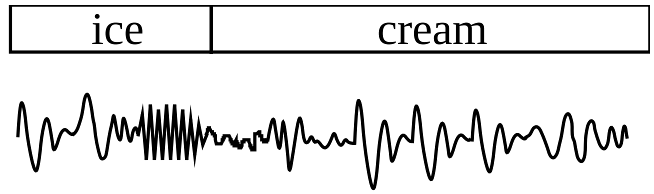
Recognition network for continuously spoken word recognition.*

Recognition and traceback

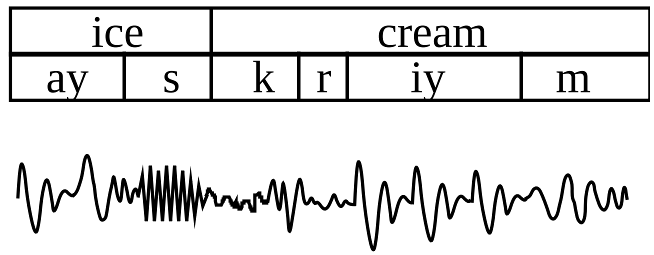


Recording word boundary decisions.*

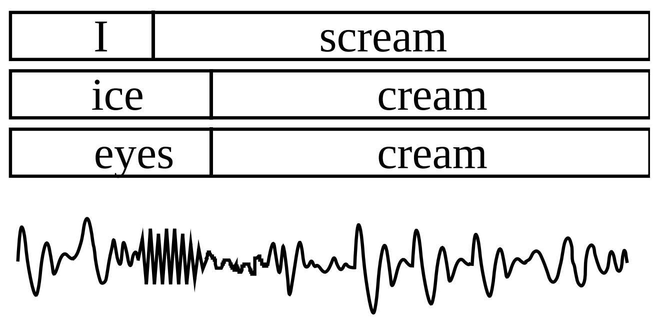
Annotation results



(a) 1-alternative, 1-level



(b) 1-alternative, 2-level



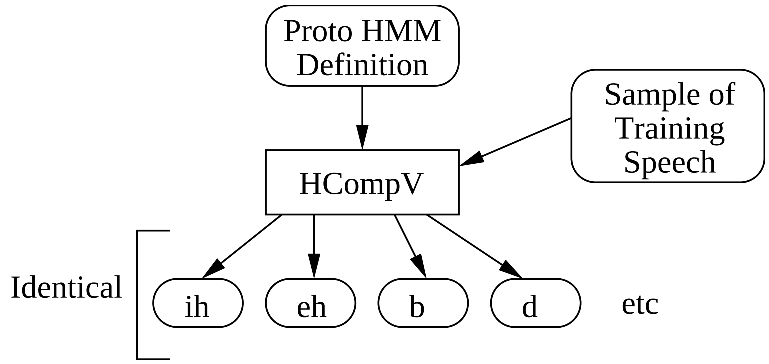
(c) 3-alternative, 1-level

Example transcriptions.*

Practical issues

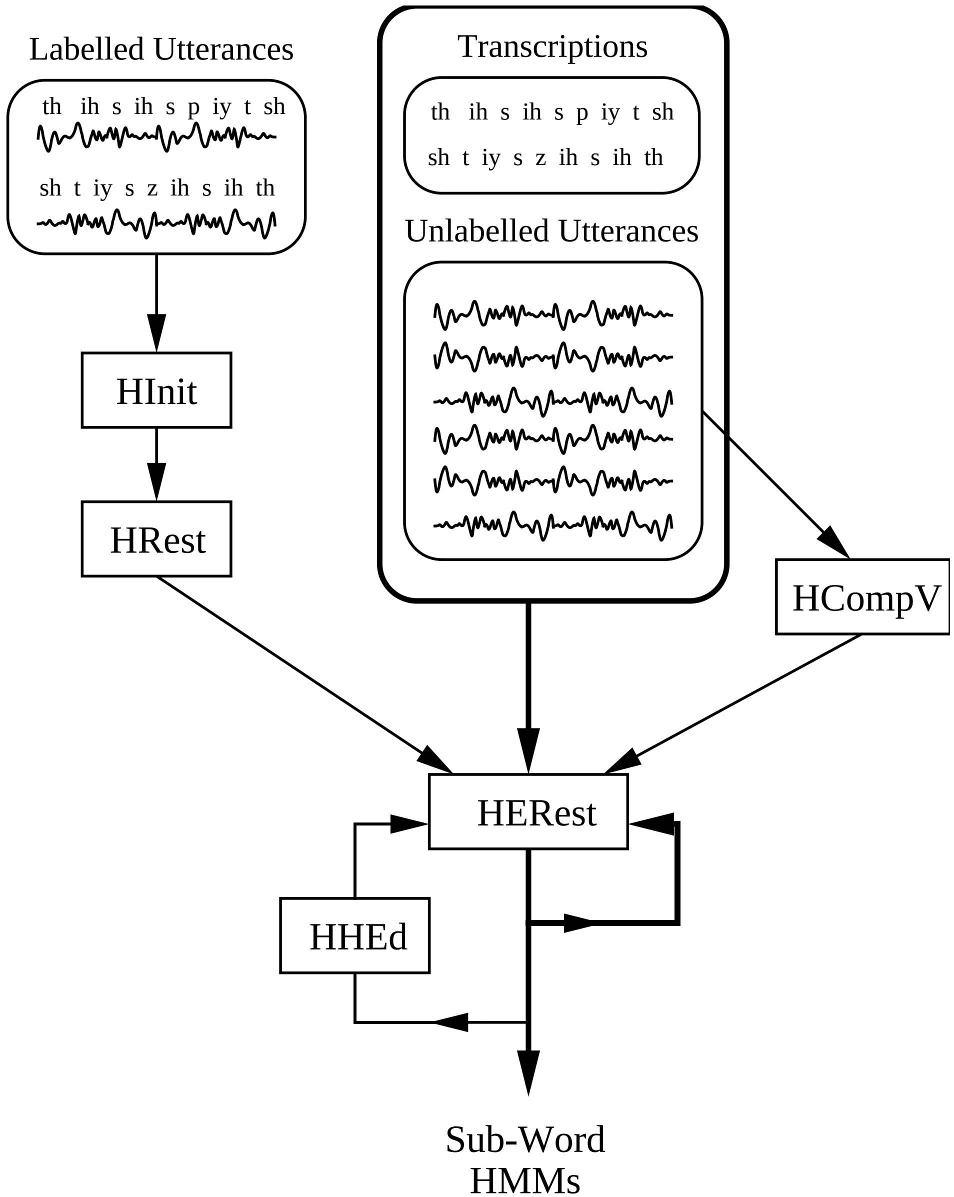
Initialisation

1. Random
2. Flat start
3. Least squares
4. Viterbi
5. Baum-Welch (supervised)
6. Baum-Welch (unsupervised)



Flat start.*

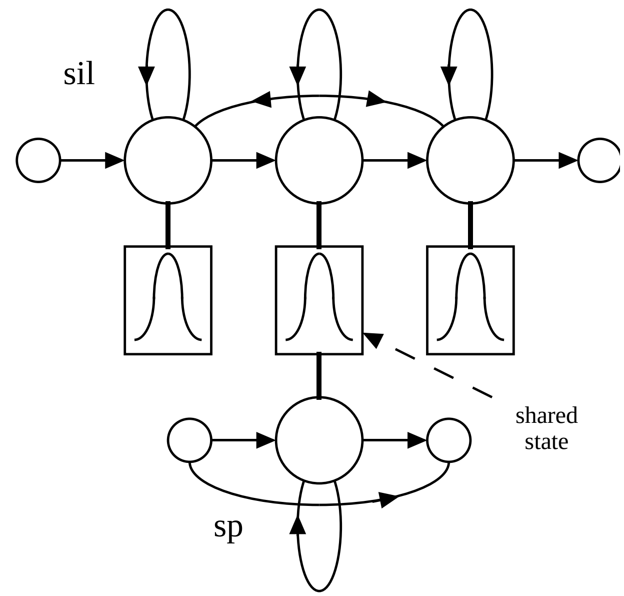
Re-estimation and embedded re-estimation



Training sub-word HMMs.*

Number of parameters

- Parsimony
  - Occam's razor
- Amount of training data



Linking the silence models.*

Regularisation

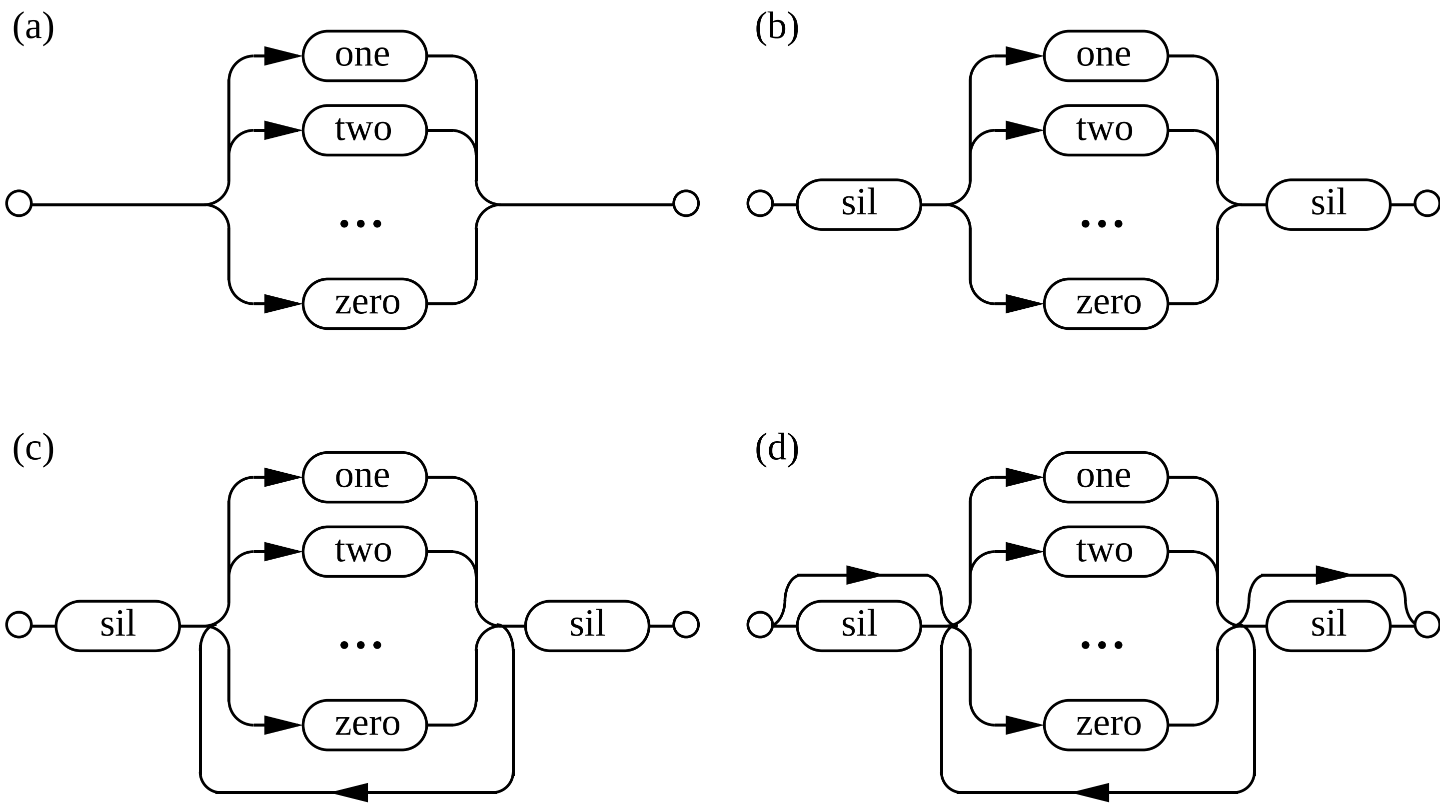
- variance floor
- parameter tying

Search strategies

- Depth first: stack decoder/A*
- Breadth first: beam pruning

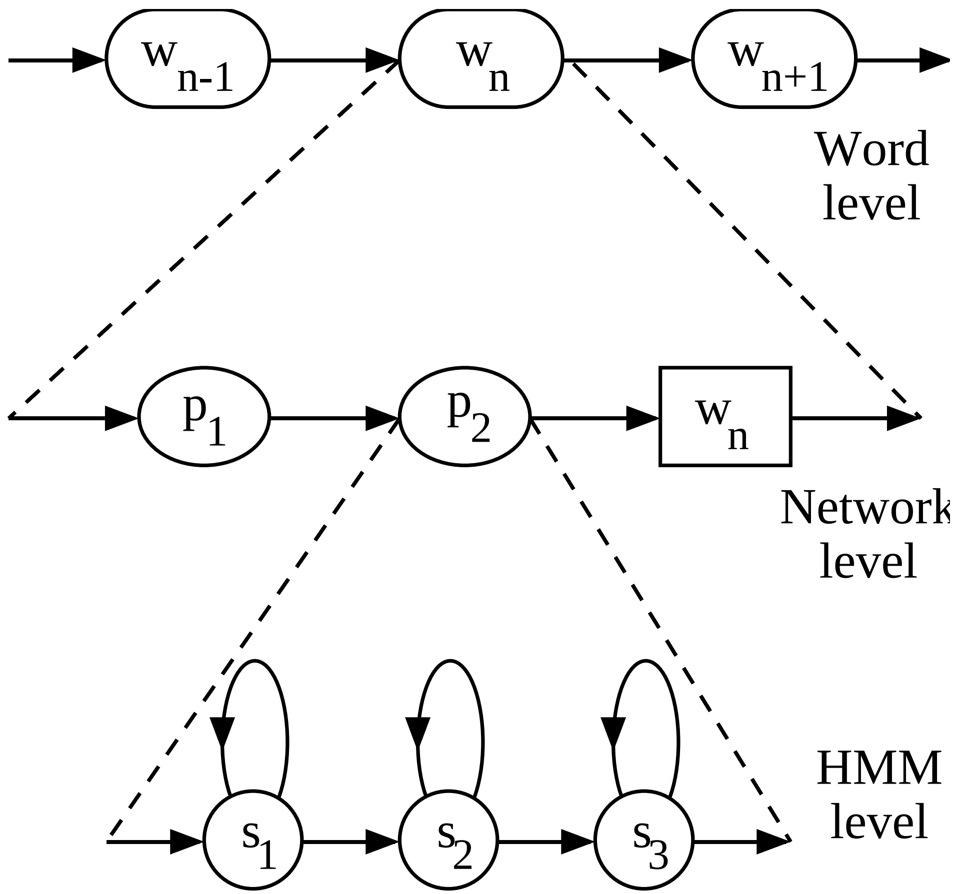
Applications in ASR

Isolated word recognition



Example digit recognition networks.*

Hierarchy of recognition networks



Recognition network levels.*

Today's summary

- Example of a simple labelling task
- Intro to HMM toolkit & practical issues
- Applications in automatic speech recognition

Further reading

F. Jelinek. *Statistical methods for speech recognition*. MIT, Cambridge MA, 1998. [ISBN 0-2621-0066-5].

S. J. Young, J. Odell, et al. *The Fundamentals of HTK*, chapter 1 in *The HTK Book*, pp. 2–13, Entropic, Cambridge, UK, 1997. [http://htk.eng.cam.ac.uk/].

S. J. Young. Large vocabulary continuous speech recognition. *IEEE Sig. Proc. Mag.* 13(5): 45–57, 1996.